CORPORATE BANKRUPTCY PREDICTION MODEL FOR INTERNET STARTUP COMPANIES

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ABSTRACT

The purpose of this paper is to present a new approach to developing a financial distress prediction model that analyzes factors affecting success or failure of dot-com companies. In a new model, both demand side and supply side categories account for the performance of firms following IPOs. Huyghebaert et al. (2000) and Lewis et al. (2000) serve as a framework for the new model. This research uses a logistic regression analysis to build the proposed model. The demand side category includes a market condition factor, while the supply side category includes a funds flow factor. The statistical results show that independent variables such as Gross Profit Margins, Cash Flows, Accounts Receivables, Accounts Payables, and Market Value are significant whereas Stockholders' Equities, Dividends, Capital Expenditures, and Inventories are insignificant.

INTRODUCTION

In 2001, many Internet start-up companies, so called Dot-Com companies went bankrupt, yet many of Internet-related start-ups are managing to get funded. McGee and Edmonston (2001) reports that about $5 billion will be invested in dot-com companies in 2001, which is not as big as $17 billion in 2000 but almost the same as in 1999. In other words, dot-com companies are not extinct, but will continue to exist. To avoid the same mistakes that they made during 1999 and 2000, venture-capital firms should be more cautious when they make investments in dot-com companies. Stock investors wonder how to distinguish a successful dot-com company from a bad one. A reliable corporate bankruptcy model is needed for investors and venture capitalists in order to evaluate the financial performance of dot-com companies. In addition, recent boom of social media companies which have similar characteristics as those Internet start-up companies in the 2001 dot-com crisis seems to warrant to learn from the past experiences.

Much research has been done on financial distress prediction models in the last three decades, and a few studies have investigated start-up firms' financial performance. Recently, a few studies have attempted to analyze financial distress of dot-com companies. Most of these studies employ explanatory variables in the supply side category such as financial measurements such as financial ratios for determining an Internet startup company's bankruptcy likelihood. According to Lewis et al. (2000), variables in the demand side category such as a market condition, an underwriter reputation affect a firm's financial performance significantly.

A survey of prior literature reveals that there is no study that accommodates both supply side category variables and demand side category variables in financial distress prediction modeling for dot-com companies. A lack of literature in this important field and a strong demand for a reliable model motivates this study. Huyghebaert et al. (2000) and Lewis et al. (2000) serve a framework for developing a new approach.

A logistic regression analysis is employed for the model development. Therefore, the purpose of this paper is to develop a financial distress prediction model that analyzes both supply side category factors and demand side factors affecting success or failure of dot-com companies, using a logistic regression analysis.

It is expected that the new approach makes a significant contribution to the financial literature and the E-Business community, and help investors make proper decisions on Internet start-up companies. Furthermore, considering many social media companies and cloud-based enterprises emerging and prospering these days, our new model can help investors make better investment decisions on the Internet-based companies. In the next section, a review of literatures on the financial distress is given. Section 3 explains a methodology for the proposed model. Statistical results are reported in Section 4, followed by discussion in Section 5. Section 6 summarizes and concludes this study.

LITERATURE REVIEW

There is considerable literature on financial distress prediction models which have focused on mature listed firms. On the other hand, research on newly established firms' survival process in the post entry period is very limited.

Literature on the long-term performance of firms following initial public offerings (IPOs) can be divided into two main categories: the demand side and the supply side categories. The demand side category studies suggest that investors are periodically overoptimistic about the potential of newly established firms (Ritter 1991; Loughran and Ritter 1995). This is especially true when young growth firms go public in high-volume years. An application of the demand side theory is Lewis et al. (2000), which reports the quality of underwriters and the market status (high vs. low volume) have significant impacts on prediction of financial distress.

The supply side category studies identify earnings-based performance measures, cash flow factors, and non-financial factors as representatives of issuers' long-term performance. Earnings-based performance measures have been employed in numerous studies (Altman 1968; Zmijewski 1984; Gilbert, Menon and Schwartz 1990; Hopwood, McKeown and Mutchler 1994; Ward and Foster 1996). Cash flows factors have been often reported in prior studies (Huyghebaert et al. 2000; Aziz and Lawson 1989; Aziz et al. 1988; Gentry et al. 1987; Casey and Bartczak 1985). Recently, non-financial factors are drawing more attention (Ueng and Lee 1996; Gartner, Starr and Bhat 1991; Flamholtz and Aksehirli 2000). Existing literature in the supply side category suggests that funds flow measures may be better than traditional financial ratios for earlier prediction of financial distress (Huyghebaert et al. 2000; Laitinen 1992; and Aziz et al. 1988).

In summary, literature shows both demand and supply side category studies are significant. This new approach of including both side factors is especially appropriate for studying the subject of this paper because most dot-com firms are established and gone public in a hot issue market. Accounting data is also very limited due to the short lives of these companies. Therefore, it is expected the prediction reliability may increase if both demand side factors and supply side factors are included in a corporate bankruptcy prediction model. However, no study has been done on developing such model. As a result, this study hypothesizes that a new model including both demand side and supply side factors shows statistically significance in predicting financial distress of Internet start-up companies.

RESEARCH METHODS

As discussed in the previous section, this study develops a statistical model that includes both demand and supply side factors, to account for the long-term performance of Internet start-up firms following IPO. In the logistic regression model, a dependent variable is a binary variable which codes 1 for a bankrupt firm and 0 for a non-bankrupt firm. Independent variables are the demand side and supply side factors.

Lewis et al (2000) and Huyghebaert et al (2000) serve as a framework for a new model. Huyghebaert et al (2000) consists of 823 Belgian start-up firms over a five-year period. Their sample includes various the industries in Belgium. In contrast to them, this study focuses on Internet start-up firms in the USA. Dot-com companies used in this study have some unique charateristics compared to the sample of Huyghebaert et al. (2000). In general, Dot-com companies are based on the Internet and information technology. This implies that these companies may not be so capital and facility intensive since dot.com companies tend to rely on a relatively small number of talented entrepreneurs.

Regarding the demand side, this paper includes market condition factor in a new model, based on the findings from Lewis et al (2000). For the supply side, a funds flow factor is employed in the proposed model, based on the findings from Huyghebaert et al. (2000). Therefore, two main factors are proposed as explanatory variables for a financial distress prediction model in this study: Market Condition Factor, Funds Flow Factor.

Statement of Cash Flows and Funds Flow Factors

As financial analysts and investor have been less valued earnings-based metrics in big accounting scandals such as Enron, WorldCom, and others, many financial statement users have leaned toward the cash flow statement. Investors have also tended to pay more attention to cash flow statement. Unlike accrual-based statements such as balance sheet and income statement, statement of cash flows provides useful information about cash inflows and outflows in detail.

Basically, companies need cash to buy inventories, raw materials, equipment, and many other items for their business operation, and to pay wages and salaries, debts, and dividends. Insufficient cash balance can lead to default on payables due and ultimate bankruptcy. In order for a company to survive or prosper should operate profitably and generate enough cash to meet its obligations. Cash flows could be more useful to creditors in predicting financially distressed firms (Ward, 1994).

Considering the importance of cash flows in predicting finical distress and bankruptcy, three measures are developed for variables describing funds flow factors: Operating Cash Flow, Financing & Investing Fund Flow and Working Capital. These measures are defined similar to Gentry, Newblood and Whitford (1987).

First, operating cash flow variable is included in a new model as a funds flow factor. It is widely accepted that liquidity constraints play an important role in business survival, especially at the start-up stage. Accordingly, firms, which are able to generate more operating cash flow during their earlier years, have higher chances of survival. To capture operating cash flows, two measures are used: Gross Margin (GM) and Residual Cash Flow (RCF). Residual cash flow is calculated by subtracting the cost of capital from the net adjusted cash flows for the accounting period. Residual cash flow is used as a proxy for cash inflow since it is a measurement that provides cash value ass a key indicator of the business performance. It is expected that the higher the gross margin and the larger the cash residual, the better the chances of survival.

Second, a new model also includes financing and investing funds flow variables for the funds flow factor. The choice between equity and debt financing and the selection of the optimum capital structure is thoroughly discussed in the finance literature. Firms that choose equity financing are less vulnerable and hence are less likely to fail. To the contrary, debt financing increases the obligations and commitments of start-up firms. Monetary obligations are of more importance and greater influence when the operating cash flows are not enough to cover the operating activities. To capture the impact of financing and investing activities, Equity Financing (EQ), Dividends (DVD), and Capital Expenditures (CAP) variables are used.

In addition, working capital variables are considered for the fund flow factor. Consistent with the operating cash flow variables, firms have greater incentive to control their working capital in order to enhance the survival chances. To capture the working capital variables, Inventories (INV), Accounts Receivables (AR), and Accounts Payables (AP) are used.

In general, capital expenditures take big amounts of investment which is usually made either by debt financing or equity financing. In addition, capital expenditures decrease cash flows which may add a chance of bankruptcy which leads to Hypothesis 4.

It is hypothesized that the higher the current assets and the lower the current liabilities, the higher the chances of survivals of start-up firms. A high dependence on current liabilities to finance operating activities increases the dependence of start-up firms on external sources and increases vulnerability to failure. Hence, the following hypotheses are tested in this paper.

H_1 *The higher gross margin is, the higher the chances of survival of start-up firms are likely.*

H_2 *The higher cash inflows are, the higher the chances of survival of start-up firms are likely.*

H_3 *The higher equity financing is, the higher the chances of survival of start-up firms are likely.*

H_4 *The higher capital expenditures are, the lower chances of survival of start-up firms are likely.*

H_5 The higher current assets are, the higher the chances of survival of start-up firms are likely.

H_6 The higher current liabilities are, the lower the chances of survival of start-up firms are likely.

Capital Market Condition Factor

Bayless and Chaplinsky (1996) reports that investors are less fearful of buying overvalued equity in high-volume issue markets. They attribute that to either the herding theory or reduced levels of information asymmetry between issuers and investors during such periods. The Herding theory suggests that investors become overly optimistic and more receptive to investing in poor-quality firms in bull markets. Accordingly, investors are expected to be less astute during hot markets. The information asymmetry interpretation assumes that busted IPOs are more likely when market conditions are poor, while the herding theory assumes that busted IPOs are more likely when market conditions are favorable (Lewis et al. 2000).

To measure the market condition, this paper uses market values of the firm as proxy for marker condition. It is hypothesized that the higher the firm's market value, the higher the chances of survivals of start-up firms. Accordingly, the third hypothesis is as follows:

H_7 The higher the market value, the higher chances of survival of start-up firms.

LOGISTIC REGRESSION MODEL

Logistic regression models are based on the logistic distributions function and are usually estimated with maximum likelihood. Logistic regression models take a binary (dichotomous) dependent variable and offer probabilities and odds for the interpretation of parameters. A binary dependent variable, probabilistic interpretation, and maximum likelihood estimation are major differences between linear regression analysis and logistic regression analysis. Probabilistic interpretation and maximum likelihood estimation are attributes differentiating logistic regression models from discriminant. Several studies in the finance area have used logistic regression models (Ueng and Lee 1996; Huyghebaert et al 2000).

Many researchers prefer logistic regression approach to discriminant model for several reasons. Logistic regression models require less vigorous assumptions in a model building process than discriminant analysis. As a result, results from logistic analysis are more robust than those from discriminant model. Second, the odd ratios from logistic model can be used as policy guidelines in investment planning in hospitals. Therefore, the use of logistic analysis seems to be an ideal tool for this study.

For this research, a logistic regression model can be written as Kleinbaum (1994):

$$P(X_k) = P(Y = k \mid X_1, X_2, ..., X_p)$$

$$= \frac{1}{1 + e^{-z}} \qquad (1)$$

$$\text{where } z = \alpha + \sum_{j=1}^{p} ß_j X_j \tag{2}$$

Y = a dichotomous dependent variable (Bankruptcy),
k = value of Y (1 = Bankruptcy, 0 = Non-bankruptcy),
X_j = independent variables (j = 1 through p),
P(X) = conditional probability of an event k occurring, and
X = a vector of independent variables.

The logistic regression model (Equation 1) can be rewritten in terms of the odds of an event occurring. The odds of an event 'k' occurring (Y = k) are then estimated as:

$$\text{Odds} = \frac{P(X_k)}{1 - P(X_k)} \tag{3}$$

With odds for each k (Equation 3), odds ratio can be determined as:

$$\text{Odds Ratio } (X_1, X_0) = \frac{\text{Odds for } X_1}{\text{Odds for } X_0} \tag{4}$$

A logit also can be computed by the odds (Equation 3) as:

$$\text{logit } P(X) = \text{Log (Odds)} \tag{5}$$

Chi-square value of model improvement will be used as a measure of model reliability.

To test the seven hypotheses developed above, the following equation is employed in the logistic regression analysis.

$$STATUS_{it} = a_0 + a_1GPM_{it} + a_2CF_{it} + a_3SHE_{it} + a_4DIV_{it} + a_5CAPEXP_{it} + a_6INV_{it} + a_5REC_{it} + a_6AP_{it} + a_7MV_{it} \tag{6}$$

where:
$STATUS_{it}$ = 1 for a bankrupt firm and 0 for a non-bankrupt firm.
GPM_{it}= Gross Profit Margins (predicted sign: -)
CF_{it}= Cash Flows (predicted sign: -)
SHE_{it}= Stock Holders' Equities (predicted sign: -)
Div_{it}= Dividends (predicted sign: ?)
$CapExp_{it}$= Capital Expenditures (predicted sign: +)
Inv_{it}= Inventories (predicted sign: -)

Rec_{it}= Receivables (predicted sign: +)
AP_{it}= Accounts Payables (predicted sign: +)
MV_{it} = Market Value (predicted sign: -)

The dependent variable, $STATUS_{it}$, is a discrete number. It will be 1 for a bankrupt firm and 0 for a non-bankrupt firm. The firm's bankruptcy status is identified in the Research Insight database. Gross Profit Margins **(**GPM_{it}) are defined as net sales minus costs of goods sold to proxy for the chance of survival as they provide resources. Cash flows are a proxy for the firm's capability to generate operating cash flows. The total stockholders' equity, dividends paid, and capital expenditures are used to proxy for the firm's financing and investing activities. Three other measures such as inventories (Inv_{it}**),** receivables **(**Rec_{it}**),** and accounts payables (AP_{it}**)** are used to proxy for working capital. Another measure, Market Value (MV_{it}) is also used as proxy for the capital market condition.

EMPIRICAL RESULTS

Descriptive Statistics

Panel A in Table 1 presents the sample selection procedures which resulted in a final sample of 374 firms based on the bankruptcy and financial data availability. Initially, a list of Initial Public Offering (IPO) firms was obtained from the Research Insight database. There are 2,741 companies listed during the time period of 1998 to 2003. Among the listed IPO firms, there are 667 Internet and high-tech related firms.

During the analysis time period, 127 firms were bankrupt while the remaining 540 firms stay in business. Unavailability of firms' data regarding their financial measures on the Research Insight (formerly COMPUSTAT) database reduces the sample to 322 non-bankruptcy firms and 52 bankruptcy firms resulting in the total of 2244 firm/year observations.

Table 1
Sample Selection

SELECTION CRITERION	Panel A: Non-bankrupt Firms	Panel B: Bankrupt Firms
Total number of IPO firms between 1998 & 2003	2741	2741
Internet and high-tech related firms	667	667
Non-bankrupt firms	540	127
Availability of COMPUSTAT data	322	52
Total Observations	322	52

Table 2a and Table 2b show descriptive statistics for the dependent and independent variables used in the logistic regression analysis for hypotheses.

Table 2a
Descriptive Statistics - Panel A: Non-bankrupt Firms

Variable	N	Mean	Median	Std Dev	Minimum	Maximum
GPM	1932	49.61	43.31	22.51	0.15	100.00
CF	1932	161.71	4.62	487.51	0	4422.28
SHE	1932	331.91	38.07	1348.83	0	26945.00
Div	1932	1.86	0.00	70.61	0	838.80
CapExp	1932	75.06	2.89	449.94	0	11146.37
Inv	1932	17.21	0.04	88.26	0	1853.00
Rec	1932	50.16	6.06	242.32	0	7346.89
AP	1932	37.71	2.87	190.21	0	5653.03
MV	1932	84.36	190.60	299.81	0	6867.12

Overall, Descriptive Statistics in Table 2a and 2b indicate that bankrupt firms tend to have much lower mean values in all the variables. This could be interpreted that in the first place bankrupt firms had much less resources than non-bankrupt firms. For example, the mean score for GPM is $49.61 million for non-bankrupt firms whereas it is $39.59 million for bankrupt firms. All other variables show the similar patterns.

Table 2b
Descriptive Statistics for Panel B: Bankrupt Firms

Variable		Mean	Median	Std Dev	Minimum	Maximum
GPM	312	39.59	28.13	22.04	0.25	98.10
CF	312	76.30	11.20	345.37	0.01	2449.00
SHE	312	179.45	23.18	505.60	0.01	4149.15
Div	312	9.02	0.00	195.93	0	3402.08
CapExp	312	54.65	4.01	161.79	0	1309.88
Inv	312	8.88	0.00	38.63	0	341.32
Rec	312	32.45	4.21	143.13	0	1835.00
AP	312	33.08	3.78	182.56	0	2438.00
MV	312	65.50	69.86	162.40	0	1261.00

The Pearson correlation coefficients for the variables in the proposed model are reported in Table 3a and Table 3b. Panel A presents correlation matrix for non-bankrupt firms in Table 3a.

Table 3a
Correlation Matrix for Panel A: Non-bankrupt Firms

	GPM	CF	SHE	Div	CapExp	Inv	Rec	AP	MV
GPM	1.0000	-0.0247	-0.0106	-0.0363	-0.0348	-0.0733	-0.0569	0.0700	-0.0294
		0.5361	0.6776	0.1356	0.1532	0.0025	0.0189	0.0037	0.2236
CF		1.0000	0.7471	0.0063	0.6734	0.3328	0.6392	0.6486	0.5705
			<0.0001	0.8751	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001
SHE			1.0000	0.0185	0.6811	0.3872	0.6470	0.6026	0.5463
				0.4303	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001
Div				1.0000	0.0144	0.0130	-0.0099	-0.0156	0.0045
					0.5181	0.5572	0.6559	0.4789	0.8398
CapExp					1.0000	0.2577	0.5229	0.6295	0.5904
						<0.0001	<0.0001	<0.0001	<0.0001
Inv						1.0000	0.5747	0.4215	0.2913
							<0.0001	<0.0001	<0.0001
Rec							1.0000	0.9018	0.6484
								<0.0001	<0.0001
AP								1.0000	0.6853
									<0.0001
MV									1.0000

Table 3b shows correlation matrix for the bankrupt firms. The coefficient values range from -0.0733 to 0.9018. This indicates that multicollinearity is not a problem.

Table 3b
Correlation Matrix - Panel B: Bankrupt Firms

	GPM	CF	SHE	Div	CapExp	Inv	Rec	AP	MV
GPM	1.0000	-0.0255	-0.0123	-0.0372	-0.0357	-0.0749	-0.0573	0.0711	-0.0291
		0.5432	0.6681	0.1401	0.1546	0.0023	0.0192	0.0035	0.2458
CF		1.0000	0.7582	0.0074	0.7458	0.3477	0.6532	0.6672	0.5841
			<0.0002	0.6843	<0.0003	<0.0001	<0.0001	<0.0001	<0.0001
SHE			1.0000	0.0173	0.6824	0.4322	0.6582	0.6548	0.5533
				0.4505	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001
Div1				1.0000	0.0237	0.0144	-0.0128	-0.0246	0.0058
					0.6211	0.4727	0.5659	0.5789	0.8574
CapExp					1.0000	0.3662	0.4512	0.6445	0.5977
						<0.0001	<0.0001	<0.0001	<0.0001
Inv						1.0000	0.5856	0.5225	0.2503
							<0.0001	<0.0001	<0.0001
Rec							1.0000	0.9001	0.6024
								<0.0001	<0.0001
AP								1.0000	0.6301
									<0.0001
MV									1.0000

Logistic Regression Analysis Results

The relationship between firm's bankruptcy status and its characteristics is examined using logistical regression analysis which analyzes a binary response variable.

Huyghebaert et al. (2000) hypothesized the direction of the flow of the fund. Following their prediction, we expect that in general there are negative relationships between cash inflows and bankruptcy whereas there are positive relationships between cash outflows and business failure. Accordingly, Table 4 shows the expected signs as used in Huyghebaert et al. (2000).

The coefficient for the bankruptcy status (STATUSit) and Gross Profit Margins (GPM) is significant at p = 0.0113 (H1). The coefficient for Cash Flows (CF) is marginally significant at p = 0.0692 (H2). The coefficient for Stockholders' Equities (SHE) and Dividends (Div) are not significant (H3). The coefficient for Capital Expenditures (CapExp) is not significant (H4). The Inventories variable is insignificant while the Receivables variable (Rec) is significant at p = 0.0069 (H5). The Account Payables variable (AP) is significant with its coefficient sign (p = 0.0032) although it is not in the proper direction (H6). The market condition variable, Market Value (MV) is marginally significant at p = 0.0618 (H7). Also, it is noted that in Table 4, the intercept term is non-zero and statistically significant. This may suggest possible omitted variables or measurement error in the regressors. Table 4 presents the results of estimating equation (6) where the dependent variable, STATUSit, is a binary (dichotomous) variable and offer probabilities and odds for the interpretation of parameters. The coefficient for Gross Profit Margin (GPM) is significant at p = 0.01 and in the proper direction (H1). The coefficient for Cash flow (CF) is significant at p = 0.06 and in the proper direction (H2). The coefficient for Receivables (rec) is also significant at p = 0.10 and has the positive sign as predicted (H5). The coefficient for Accounts Payable (AP) is significant at p = 0.003 and has a negative sign as expected (H6). The coefficient for Market Value (MV) is significant at p = 0.06 which suggests incremental explanatory power. All other coefficients are insignificant.

The results suggest that hypotheses H1 and H2 are supported. It indicates that financially healthy firms with higher operating cash flows are more likely to survive than financially unhealthy firms. However, hypotheses H3 and H4 are not supported as indicated with insignificant results. Thus, financing and investing funds flow variables are not significantly related to the firm's survival. Table 4 provide mixed results on H5. Account receivables is significant, yet inventory is not. Results on H5 and H6 suggest that current assets and liabilities play vital roles in the start-up company survival.

Table 4
Logistic Regression Analysis Results

Pseudo $R^2 = 0.028$, χ^2 (d.f.= 6) = 15.654 ($p < 0.001$)

YEAR	Expected Sign	Estimated Parameter	p-value
INTERCEPT		0.154	0.0001
GPM	-	0.0001	0.0113
CF	-	0.0004	0.0692
SHE	+	0.0001	0.8761
Div	?	-0.0007	0.2280
CapExp	+	-0.0004	0.3253
Inv	+	-0.0011	0.5558
Rec	+	0.0059	0.0069
AP	+	-0.0027	0.0032
MV	+	0.0001	0.0618

Sensitivity Analysis

The robustness of the results in Table 4 is also checked by alternative measures of the independent variable, GPM (Gross Profit Margins) and the market condition factor, MV (Market Value). Net income instead of gross profit margin and total sales rather than market value are included in the logistic regression model equation 1 and the same analyses are repeated. Table 5 shows the results. The results are basically similar to those reported in Table 4.

In addition, to further check the robustness of the results we used working capital and other current assets instead of cash flows and receivables, respectively. The results are basically similar to those reported in Table 4 and 5.

Table 5
Robustness Check – Panel A

Pseudo $R^2 = 0.025$; χ^2 (d.f. = 6) = 14.727; $p < 0.001$

Year	Expected Sign	Estimated Parameter	p-value
Intercept		0.175	0.0001
NI	-	0.0001	0.0125
CF	-	0.0003	0.0752
SHE	+	0.0001	0.8945
Div	?	-0.0006	0.2462
CapExp	+	-0.0004	0.3277
Inv	+	-0.0012	0.5577
Rec	+	0.0055	0.0071
AP	+	-0.0025	0.0035
Sales	+	0.0001	0.0654

Note: NI = Net Income; CF = Cash Flows; SHE = Stockholders' Equities; Div = Dividends; CapExp = Capital Expenditures; Inv = Inventories; Rec = Receivables; AP = Accounts Payables;

CONCLUSION

In summary, this paper proposes a new approach to predict a corporate bankruptcy for Internet startup companies, by accommodating both demand side and supply side variables. The proposed logistic regression model includes a funds flow factor for the supply side and a market condition factor for the demand side.

There are a lot of areas for improvement for further studies on this topic. Due to the data availability and time constraint, this paper has not included most recent data. Therefore, a future study is suggested to generate empirical evidence from data analysis by collecting recent data from the stock markets and other data warehouses. In addition, the demand side category can add a new factor such as underwriter reputation. A funds flow factor in the supply side category also can add new variables.

In conclusion, this study makes a contribution to the financial literature and the E-business community by providing a new approach that help investors make proper decisions on Internet start-up companies. Furthermore, considering many social media companies and cloud-based enterprises emerging and prospering these days, our new model can help investors make better investment decisions on the Internet-based companies. It is also expected that the e-business community as well as investors can benefit from the empirical evidence from this paper by enhancing efficiency and effectiveness in equity investment.

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